

1 Investigation into the use of satellite data in aiding characterization of particulate air quality in
2 the Atlanta, Georgia metropolitan area

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30 **ABSTRACT**

31 Poor air quality episodes occur often in metropolitan Atlanta, Georgia. The primary focus of this
32 research is to assess the capability of satellites as a tool in characterizing air quality in Atlanta.
33 Results indicate that intra-city PM_{2.5} concentrations show similar patterns as other U.S. urban
34 areas, with the highest concentrations occurring within the city. Both PM_{2.5} and MODIS AOD
35 show more increases in the summer than spring, yet MODIS AOD doubles in the summer unlike
36 PM_{2.5}. A majority of OMI AI is below 0.5. Using this value as an ambient measure of
37 carbonaceous aerosols in the urban area, aerosol transport events can be identified. Our results
38 indicate that MODIS AOD is well correlated with PM_{2.5} on a yearly and seasonal basis with
39 correlation coefficients as high as 0.8 for Terra and 0.7 for Aqua. A possible alternative view of
40 the PM_{2.5} and AOD relationship is seen through the use of AOD thresholds. These probabilistic
41 thresholds provide a means to describe the AQI through the use of past AOD for a specific area.
42 We use the NAAQS to classify the AOD into different AQI codes, and probabilistically
43 determine thresholds of AOD that represent the majority of a specific AQI category. For
44 example, the majority 80% of moderate AQI days have AOD values between 0.5 - 0.6. The
45 development of thresholds could be a tool used to evaluate air quality from the use of satellites in
46 regions where there are sparse ground-based measurements of PM_{2.5}.

47 **IMPLICATIONS**

48 Satellites can be used successfully as a tool for characterizing air quality on an urban scale.
49 Statistical analysis of multi-year satellite data can yield a useful and easily understandable way
50 of describing air quality through satellite derived AQI. In areas without many monitoring sites of
51 PM_{2.5}, this approach could be useful to those air quality forecasters. Additionally, the use of
52 satellite thresholds could increase satellite utility beyond that of qualifying events for exclusion
53 using the U.S. EPA's exceptional event rule in determination of attainment of the NAAQS.

54 **INTRODUCTION**

55 Any person flying into Atlanta, Georgia's Hartsfield-Jackson Atlanta International
56 Airport during the summer will see first-hand the visible effects of poor air quality in Atlanta.
57 Atlanta has the highest population density in the southeastern U.S. making it one of the larger
58 urban areas in the contiguous U.S. (<http://www.census.gov/popest/metro/metro.html>). The

59 metropolitan area is comprised of 28 counties, with the city boundary contained mostly within
60 Fulton County. High population density and large amounts of environmental toxins have placed
61 Atlanta at the top of Forbes's Most Toxic City List for 2009
62 (<http://www.forbes.com/2009/11/02/toxic-cities-pollution-lifestyle-real-estate-toxic-cities.html>).
63 The American Lung Association declares Atlanta as the 17th worst city for year-round particle
64 pollution ([http://www.stateoftheair.org/2009/city-rankings/polluted-cities-particle-pollution-](http://www.stateoftheair.org/2009/city-rankings/polluted-cities-particle-pollution-year.html)
65 [year.html](http://www.stateoftheair.org/2009/city-rankings/polluted-cities-particle-pollution-year.html)). This study considers particle pollution as a mixture of small particles and liquid drops
66 that have aerodynamic diameter less than 2.5 μm ($\text{PM}_{2.5}$). Epidemiological studies in Atlanta
67 have linked increases in particle pollution to increased asthmatic pediatric emergency room visits
68 ¹, while Peel et al. ² found that the risk of death increased for hypertensive people in cases of
69 elevated PM_{10} .

70 Assessment of air quality is commonly based on averages of 24-hour data from ground-
71 based measurements of $\text{PM}_{2.5}$ performed at dedicated monitoring sites. The use of 24-hour
72 average $\text{PM}_{2.5}$ data is to relate concentrations to the air quality index (AQI), which relates the
73 level of air pollution to possible health effects. The AQI is used to disseminate information about
74 air quality to the public via different methods of media, e.g., local television news, radio or
75 newspaper (Table 1). The AQI is scaled to relate the $\text{PM}_{2.5}$ concentrations to the National
76 Ambient Air Quality Standard (NAAQS)³. Through the Clean Air Act of 1990, the U.S. EPA has
77 the authority to set national air quality standards to protect the public health. In 2006, the U.S.
78 EPA strengthened the NAAQS by reducing the 24-hour standard from 65 $\mu\text{g}\text{m}^{-3}$ to 35 $\mu\text{g}\text{m}^{-3}$. In
79 doing so, the AQI must now be revised to reflect the changes in the NAAQS, and this action by
80 the EPA is currently under review. Table 1 gives the old AQI and the proposed AQI revisions.
81 These changes will certainly affect a city's proportion of good, moderate, and unhealthy days.
82 The $\text{PM}_{2.5}$ measurements that are used for AQI forecasts provide high temporal resolution, but
83 lack spatial resolution and coverage. In a large metropolitan area like Atlanta with only seven
84 monitoring sites for forecast purposes, the lack of spatial resolution has implications for air
85 quality forecasts and impacts.

86 Satellite data has been thought of as a means to address the lack of spatial coverage by
87 monitoring sites. Satellite observations can be used to characterize aerosols, identify aerosol
88 transport, and identify cases of biomass burning⁴⁻⁷. Studies that relate satellite measurements to
89 $\text{PM}_{2.5}$, generally use the aerosol optical depth (AOD) retrieved from the NASA MODIS

90 (Moderate Resolution Imaging Spectroradiometer) instrument. AOD is a measure of light
91 extinction through the atmosphere for a given wavelength. Engel-Cox et al. ⁸ completed one of
92 the first nationwide studies that presented results of the relationship between PM_{2.5} and AOD.
93 They demonstrated that the relationship varied by region, and the east coast of the U.S. had the
94 highest correlation between AOD and PM_{2.5}. Further highlighting this regional perspective is the
95 work of Al-Saadi et al. ⁹, which developed a methodology for applying AOD maps over maps of
96 PM_{2.5} concentrations for the entire U.S. to improve air quality forecasts through the IDEA
97 (Infusing satellite Data into Environmental Applications) website
98 (<http://www.star.nesdis.noaa.gov/smcd/spb/aq/>). Recently published work by Zhang et al. ¹⁰
99 updated the methodology of the IDEA website to account for the regional nature in the
100 PM_{2.5}/AOD relationship. Gupta and Christopher ¹¹ conducted a five-year study into assessing the
101 relationship between AOD and PM_{2.5} for most of the southeast U.S. The reported correlations
102 showed a high degree of agreement, yet there was still interstate and intrastate variation.

103 Using an established methodology for relating PM_{2.5} to AOD, other researchers focused
104 on this relationship on a city-scale. Hutchinson et al. ¹² report that MODIS was adept at
105 describing an aerosol transport event that impacted air quality in parts of Texas. Research from
106 the southern U.S. found that in Birmingham, AL, satellite data were well correlated with surface
107 PM_{2.5} measurements with a correlation coefficient as high as 0.7 ^{13, 14}.

108 Most recently, Hoff and Christopher ¹⁵ provided an in-depth critical review of the field.
109 Their study outlines issues that can prohibit wider applicability of satellite data for air quality
110 studies. One issue is the spatial mismatch between satellite data and the PM_{2.5} monitoring sites
111 that provide point measurements. When stations are located closely together, it is likely that
112 those sites will occur in the same satellite pixel that reduces the number of independent
113 observations per station. Another issue lies in the assumptions used for satellite retrievals. The
114 satellite science teams are constantly making updates to their retrieval algorithms to better
115 represent the regionality of aerosol composition. AOD does not provide information about the
116 location of aerosols within the atmospheric column. Aerosols that are transported into an area
117 can be located higher in the atmosphere, where ground-based monitors do not detect it, but
118 satellites do. Instances such as this cause a mismatch between what the satellite and ground-
119 based monitors observe. Ultimately, one conclusion from Hoff and Christopher (2009) is that
120 reducing the uncertainty of the PM_{2.5}/AOD through statistical regressions is unlikely, which is

121 why we propose using a statistical analysis of AOD that directly relates to AQI bypassing the
122 $PM_{2.5}/AOD$ regression.

123 In this study, hourly and 24-hour averaged $PM_{2.5}$ measurements from seven $PM_{2.5}$
124 stations across the metro Atlanta area are analyzed along with MODIS AOD from March 1-
125 August 31, 2004 – 2008. From the hourly data, subsets are created to coincide with Terra and
126 Aqua satellite overpasses. Another satellite instrument used in this study is the Ozone
127 Monitoring Instrument (OMI). This instrument provides measurements of aerosols in the UV-
128 region of the electromagnetic spectrum. OMI performs many functions; however, of most
129 interest to this study is its ability to detect light absorbing aerosols over land¹⁶.

130 Here, we examine the applicability of satellite data to characterize representative urban
131 aerosols in Atlanta. The specific goals of this research are to (1) determine the variability of
132 $PM_{2.5}$ and satellite data on a yearly and seasonal basis; (2) assess the robustness of the $PM_{2.5}$ -
133 AOD relationship through linear regressions; and (3) statistically identify AOD thresholds that
134 can prescribe air quality directly through AQI. We will also determine the effect of the new AQI
135 designations in prescribing air quality through AOD thresholds.

136 **DATA AND METHODOLOGY**

137 **$PM_{2.5}$ Monitoring Stations**

138 As mentioned previously, the EPA makes determinations of whether states meet the
139 NAAQS for particulate matter. That standard states that in order to receive attainment for daily
140 $PM_{2.5}$, the 98th percentile of the three-year average at each pollution monitor cannot exceed 35
141 $\mu\text{gm-}3^{-3}$. States usually own and operate a network of continuous measurements that are used
142 primarily for air quality forecasts and air quality alerts. For this study, we obtained one-hour and
143 24-hour measurements of $PM_{2.5}$ from seven metro Atlanta Tapered-Element Oscillating
144 Micobalances (TEOMs) from March 1 – August 31, 2004–2008, from the Georgia Department
145 of Natural Resources, Ambient Monitoring Program (AMP)
146 (<http://www.air.dnr.state.ga.us/amp/>). The type of measurements used in this research are not
147 used for that determination; however, the Ambient Monitoring Program (AMP) assigns an
148 exceedance whenever their 24-hour averaged TEOM-based $PM_{2.5}$ measurements exceed the
149 NAAQS daily standard of 35.5 $\mu\text{gm-}3^{-3}$. Five out the seven stations have data for the entire period;

150 however, two stations (Confederate Ave. and Walton) only have data for 66% of 2005. These
151 seven stations cover three types of locations; urban – Confederate Ave., suburban – Gwinnett, S.
152 DeKalb, McDonough, and rural – Newnan, Walton, Yorkville. The $PM_{2.5,24}$ dataset is a moving
153 average that uses the current hour’s concentrations and the past 23 hours’ concentrations. Two
154 data sets were created for pairing with MODIS satellite observations, which have different
155 equatorial crossing times. To match MODIS on Terra, hourly measurements from 10 and 11 am
156 were averaged together to create the dataset $PM_{2.5,T}$. Similarly for MODIS on Aqua, hourly
157 measurements from 1 and 2 pm were averaged together to create the dataset $PM_{2.5,A}$. Analyses
158 are performed using all 3 $PM_{2.5}$ datasets ($PM_{2.5,24}$, $PM_{2.5,T}$ and $PM_{2.5,A}$).

159 **MODIS Data**

160 The MODERate Resolution Imaging Spectroradiometer (MODIS) instrument flies
161 onboard two of NASA’s Earth Observing System (EOS) satellites. The first MODIS instrument
162 is on the Terra platform, and the second MODIS instrument is on the Aqua platform. Terra flies
163 in descending polar orbit with an equatorial crossing time of approximately 10:30 am; while
164 Aqua, flies in ascending polar orbit with an equatorial crossing time of approximately 1:30 pm.
165 Generally, the satellites have overpass times over Georgia 5 -15 minutes after their equatorial
166 crossing times. Both satellites orbit 700 km above the Earth in low earth orbit, and they have
167 near global coverage daily.

168 MODIS passively measures reflected radiances from Earth across a broad wavelength
169 spectrum. It primarily uses three wavelength channels (0.47, 0.66 and 2.12 μm) to measure
170 atmospheric aerosols over land¹⁷. We use over five GB and 3700 files of Collection 5 data from
171 NASA’s Level 1 and Atmosphere Archive and Distribution System (LAADS). Collection 5 is
172 the most recent release of the data products from the MODIS science team. The analysis is
173 performed with MODIS Level 2 data, which have a resolution of $10 \times 10 \text{ km}^2$. The variable of
174 most importance to this study is “Optical_Depth_Land_and_Ocean” at the $0.55 \mu\text{m}$ wavelength.
175 AOD is an unitless measure of the amount of light attenuation over a set distance, i.e., path.
176 AOD can vary between 0 and 5, with values above unity being ascribed as heavy haze, biomass
177 burning, or dust⁸.

178 Following similar methodologies from Gupta and Christopher¹⁸ and Engel-Cox et al.⁸,
179 satellite data are matched with station data using a 0.5° degree box around each ground station.
180 Only days where both data types are available are considered for additional correlation analysis.

181 The time period of March 1 – August 31, 2004–2008, is considered for this research. Thus each
182 MODIS instrument has seven different datasets that correspond to the AOD measurements over
183 the seven ground-based PM_{2.5} measurement stations. Another dataset is created for comparisons
184 with the OMI sensor, i.e., city-scale AOD. This dataset is considered to be Atlanta AOD and
185 covers a lat/lon box of 33 – 34.5° N and 83.5 – 85.3°W. Additionally the time period for this
186 dataset matches the OMI dataset.

187 **OMI Data**

188 The Ozone Monitoring Instrument (OMI) takes measurements in the near-ultraviolet
189 (UV) for retrievals of gases and aerosols ¹⁶. OMI flies onboard the NASA satellite Aura. Aura
190 and Aqua (MODIS) fly together in a satellite constellation called A-Train. A great advantage of
191 the satellite constellation is multiple measurements made from different sensors within 15
192 minutes of each other.

193 In this study we consider the aerosol products only, primarily the UV Aerosol Index (AI).
194 The time period of March 1- August 31, 2005–2008, is considered, which is one year shorter
195 than the PM_{2.5} and MODIS data because Aura did not launch until July 2004. OMI data were
196 obtained from the NASA GSFC DAAC. The most recent release of data is in Collection 3. The
197 OMI instrument has a swath of 2600 km and provides mostly global coverage daily. Aerosol
198 products are retrieved at a spatial resolution of 13 x 24 km at nadir, however the spatial
199 resolution increases at the extremes of the satellite swath ¹⁶. In the presence of UV-absorbing
200 aerosols, the AI has positive measures with values above 0.5 considered significant ⁶. Due to
201 OMI's larger footprint, it is difficult to match OMI measurements with specific station locations.
202 Thus OMI measurements are taken for a lat/lon box of 33 – 34.5° N and 83.5 – 85.3°W.
203 Although, AI is a qualitative measure, it does provide information about the spatial pattern of
204 UV-absorbing aerosols over land. This data product is uniquely able to identify the carbonaceous
205 aerosols associated with biomass burning and urban pollution.

206 **RESULTS**

207 **Characterization of urban aerosols through PM_{2.5}**

208 We first want to determine the variability of PM_{2.5} on a yearly and seasonal basis. The
209 analysis of yearly means reveals that there is year-to-year variability within all three PM_{2.5}

210 datasets ($PM_{2.5,T}$, $PM_{2.5,A}$ and $PM_{2.5,24}$). Barplots of the five years of selected months (1 March –
211 31 August) of the $PM_{2.5,A}$ and $PM_{2.5,T}$, $PM_{2.5,24}$ datasets for Gwinnett (33.96°, -84.07°) and
212 Newnan (33.40°, -84.74°) sites are shown in Figure 1 (A & B). Gwinnett and Newnan are used
213 to contrast differences between urban/suburban vs. rural stations. These barplots display how
214 $PM_{2.5}$ averages varied over the study period. The years of 2006 and 2007 have the highest means
215 for all seven sites. The means for each year all the stations are shown in Table 1; though we only
216 consider spring and summer, our $PM_{2.5}$ averages agree well other published work of $PM_{2.5}$ in
217 Atlanta¹⁹. The years 2004 and 2008 are below the five-year average, while 2006 and 2007 are
218 the highest above the five-year average for Gwinnett, and 2005–2007 are the highest above the
219 five-year average for Newnan. $PM_{2.5,24}$ for all stations is in between $PM_{2.5,T}$ and $PM_{2.5,A}$, but it
220 behaves similarly to the other $PM_{2.5}$ datasets. Both Table 1 and Figure 1 (A&B) show that the
221 average $PM_{2.5}$ concentrations vary about $10 \mu\text{gm}^{-3}$ from each other. There are some instances
222 where the difference between $PM_{2.5,A}$ and $PM_{2.5,T}$ are significant for $\alpha = 0.05$, and those
223 instances are bolded in Table 1. Edgerton et al.¹⁹ found that during the day, hourly
224 measurements can vary by as much as $50 \mu\text{gm}^{-3}$ in the Atlanta area comparable to observations
225 in this study

226 $PM_{2.5}$ data show a distinct seasonality having higher values in the summer compared to
227 spring. Figure 1 (C and D) show seasonal averages of the three $PM_{2.5}$ datasets for Gwinnett and
228 Newnan. During the spring at Gwinnett, $PM_{2.5,T}$ varies from around $15 - 21 \mu\text{gm}^{-3}$, $PM_{2.5,A}$
229 varies between $10 - 14 \mu\text{gm}^{-3}$, and $PM_{2.5,24}$ varies between $13 - 16 \mu\text{gm}^{-3}$. Summer averages show
230 increases of 30 – 45% over spring averages. All stations show similar values. The similarity
231 between stations is shown through timeseries analysis of $PM_{2.5}$ (not shown), and the analysis also
232 indicates that summer has more variability than spring. Research by Butler et al.²⁰ and Edgerton
233 et al.²¹ provide additional information on seasonality of $PM_{2.5}$ in metro Atlanta. However, there
234 is recent work that hypothesizes that secondary organic aerosols (SOA) which have a
235 summertime maximum could be a previously underestimated portion of $PM_{2.5}$ ²². It should be
236 noted that the reduced seasonality of 2007 is likely a product of the late spring wildfire of 2007,
237 which produced the additional influx of aerosols to the metro area²³.

238 We have discussed the yearly and seasonal trends within the $PM_{2.5}$ data; however, we
239 also want to understand how each of the satellite-overpass datasets relate to each other and to
240 $PM_{2.5,24}$. To assess the similarity between $PM_{2.5,T}$ and $PM_{2.5,A}$ we created scatterplots of the two

241 datasets and calculated linear regression statistics. Scatterplots of $PM_{2.5,A}$ vs. $PM_{2.5,T}$ for 2004–
242 2008 and all years combined are shown in Figure 2. Correlation coefficients (r or r -values)
243 between $PM_{2.5,T}$ and $PM_{2.5,A}$ vary around 0.78 – 0.85. The coefficient of determination (R^2),
244 which is a measure of variance, varies between 0.61 – 0.72. When seasonality was examined
245 between these two datasets, the summertime showed higher r -values than spring. Our results are
246 consistent with Butler et al ²⁰, which shows diurnal variation of $PM_{2.5}$ in Atlanta as a function of
247 season, and during the summer the diurnal variation is less pronounced than during other
248 seasons. From these statistical measures we conclude that both datasets have similar
249 observations, but there are instances where the diurnal cycle and meteorology change the
250 conditions between Terra and Aqua. When the $PM_{2.5,24}$ dataset is compared to the $PM_{2.5,A}$ and
251 $PM_{2.5,T}$ datasets, statistics show that they are well correlated with r -values between 0.65 – 0.83.
252 $PM_{2.5,T}$ correlates slightly better than $PM_{2.5,A}$, but 30% of the variance shown by the satellite-
253 overpass datasets is not represented in the 24-hour average. This could have implications for
254 studies that relate MODIS AOD to the 24-hour average of $PM_{2.5}$.

255 We have shown that during our study period the $PM_{2.5}$ concentrations across metro
256 Atlanta are similar but have differences due to location. A majority of stations have their highest
257 means during 2006 and 2007, with 2004 and 2008 as local minima. The year 2007 was
258 dominated by a wildfire that changed the nature of $PM_{2.5}$ in Atlanta by lessening the difference
259 between spring and summer seasons. Across all stations summer months have increased $PM_{2.5}$
260 concentrations as shown by increased means and variances. Additionally, we have shown that
261 $PM_{2.5,24}$ captures 70% of the variability within the satellite-overpass $PM_{2.5}$ datasets; this could
262 impact the strength of the AOD and $PM_{2.5}$ correlations. For instance, during short (hours)
263 duration exceedance events, the $PM_{2.5}/AOD$ correlation will be lower if $PM_{2.5,24}$ is considered
264 rather than hourly data centered around the satellite overpass. In the following section we will
265 compare satellite measurements to the $PM_{2.5}$ measurements to determine how well the satellites
266 capture the $PM_{2.5}$ behavior spatiotemporally.

267 **Characterization of urban aerosols with satellite products (MODIS AOD and OMI AI)**

268 In this section, we focus upon comparing the variability of MODIS AOD to $PM_{2.5}$ and we
269 assess OMI's ability to characterize urban aerosols in Atlanta. Over 5GB and 3700 files of
270 MODIS AOD data were analyzed. In comparing yearly averages of MODIS Terra to MODIS
271 Aqua, Aqua has higher AOD at all stations for 2004-2006 and 2008. However, in 2007 Terra is

272 markedly higher than Aqua. This finding is different from the $PM_{2.5}$ yearly averages where
273 $PM_{2.5,T} > PM_{2.5,A}$, which might imply that Terra should record higher values of AOD, yet this is
274 not the case. Yearly averages of MODIS AOD at Gwinnett and Newnan are presented in Figure
275 3 (A and B). Like the trend shown in Figure 1 (A and B), MODIS AODs have their highest
276 averages in 2006 and 2007 and minima in 2004 and 2008. Aerosols that are trapped within a
277 shallow boundary layer are more difficult to assess from space than well-mixed aerosols within a
278 deep planetary boundary layer (PBL) typically found in the early afternoon¹⁴.

279 From a seasonal perspective, MODIS AOD has higher summer averages than spring
280 averages, which is in agreement with $PM_{2.5}$ (see Figure 1 (C and D)). In fact, for many cases the
281 summertime AOD as shown in Figure 3 (C and D) is almost double that of the springtime, yet
282 this doubling is not found in the $PM_{2.5}$ record. Barplots of seasonally averaged AOD from
283 MODIS at Gwinnett and Newnan are shown in Figure 3 (C and D). Our results indicate that the
284 difference between Aqua and Terra spring AOD is smaller than the difference between the two
285 during the summer. However, examination of the $PM_{2.5}$ record yields that the largest difference
286 between the datasets occurs during the spring rather than the summer. Goldstein et al.²⁴
287 hypothesize that the high summertime AOD values are driven by SOA from biogenic volatile
288 organic compounds (BVOC) that occur aloft within the ABL thus not impacting surface mass
289 measurements of $PM_{2.5}$.

290 Our previous analysis focused on AOD at specific stations, but we want to establish
291 background levels of absorbing aerosols in Atlanta to determine if there is any relationship
292 between MODIS AOD and OMI AI. We conduct the following analysis using city-scale datasets
293 (see OMI Section for explanation). $PM_{2.5}$ in Atlanta is mostly carbonaceous in nature with 35.9%
294 being organic carbon and 8.9 % being black carbon. The other dominant species is sulfate which
295 comprise 25.3% of average $PM_{2.5}$ mass²¹. Aerosols in the U.S. southeast are small in diameter
296 and are predominantly light-scattering. Maps of time averaged (March 1- Aug 31) Angstrom
297 exponent from MODIS (not shown) confirm this result with values ranging from 1 – 1.6. Since
298 the background is predominately made of light scattering particles, AI will be in a unique
299 position to detect absorbing aerosols against this background. Averages of OMI AI show little
300 variability from year to year, with a slight maximum occurring in 2007. As viewed from space,
301 the carbonaceous portion of urban aerosols in Atlanta is fairly constant around 0.3 for 2005 –
302 2008. Also, across all years a majority (80%) of AI values are below 0.5. Using the yearly

303 average or 80% cutoff to establish background conditions of Atlanta implies that if AI rises
304 above these values it could be indicative of aerosol transport.

305 OMI AI does not appear to have the same seasonality as MODIS AOD. The mean and
306 median values of AI vary little between spring and summer. Scatterplots of OMI AI vs. MODIS
307 AOD Terra/Aqua are shown in Figure 4 to access the relationship between the datasets. As seen
308 in Figure 4, there is not a discernable linear relationship between the AI and AOD. One feature
309 shown in Figure 4 is that the same AI values correspond to lower AOD values in the spring and
310 higher AOD values in the summer, which implies that any improvement of the AI/AOD
311 relationship is solely due to larger AOD associated with summer. The lack of a linear
312 relationship results in very low correlation coefficients as shown in Table 2. The correlation
313 analysis of OMI and MODIS yielded low linear correlation values shown in Table 2. Having
314 shown that AI and AOD are not related further substantiates the effectiveness of AI as an
315 indicator for transport events. For instance, the small box in Figure 4(A) shows that AI is almost
316 1.4, but AOD is around 0.3 on 13 April 2005. There are no PM_{2.5} exceedances on this day, and
317 considering that AI is sensitive to aerosol height this implies that the transport is occurring above
318 the PBL. This is an example of smoke remnants being transported into the area from the western
319 U.S. Another example occurs in 2007 (see box in Figure 4C), where smoke aerosols are
320 transported into the area. There were large active wildfires in Idaho and Montana during the time
321 period August 2007. Those wildfires caused a large haze event across the eastern U.S. During
322 this event there were PM_{2.5} exceedances in Atlanta on 13, 15-18 August 2007. The carbonaceous
323 aerosols detected by OMI on 14 August are aloft and most likely become entrained in the ABL
324 on the following days. Jacob and Winner²⁵ conclude that wildfires could become an important
325 and more frequent contributor to PM_{2.5}. The aerosols associated with this additional aerosol
326 burden will most likely be carbonaceous in nature, and the baseline of AI already established
327 would help to better assess the impact these potential wildfires will have on air quality.

328 We have shown that satellites adequately describe the general nature of urban aerosols in
329 the metro Atlanta area. Though there are some differences between what times of day results in
330 the highest values, the overall patterns of MODIS AOD match well with the PM_{2.5} observed
331 patterns on a yearly and seasonal basis. OMI AI allowed us to identify specific cases of aerosol
332 transport into the metro area by detecting the absorbing signature associated with these events.

333

PM_{2.5} and AOD Analysis

334
335 We perform a statistical analysis to assess the PM_{2.5}/AOD relationship in the Atlanta
336 metropolitan area. Figure 5 presents a linear relationship between MODIS Terra and Aqua. The
337 two satellites are well correlated with r-values > 0.78. While the coefficients of determination for
338 the different years are above 0.6, the diurnal loading of aerosols, meteorological conditions, and
339 boundary layer dynamics as well as technical issues between the two satellite instruments are all
340 possible reasons why the R²-values are not higher. During the summer in Georgia, the timing of
341 convective systems growth often occurs in the early afternoon, which coincides with Aqua's
342 overpass. In this study, MODIS Aqua has fewer observations than MODIS Terra, but both
343 satellites have between 50 – 65% data available. Other U.S. locations have shown similar
344 satellite data loss²⁶.

345 Across all seven stations and for both satellites, a majority of the points lie below the
346 NAAQS exceedance standard of 35 µg m⁻³ and have AOD less than 0.7 as represented in Figure
347 6. Scatterplots of PM_{2.5} vs. MODIS Terra and Aqua at Gwinnett and Newnan are shown for each
348 year in Figure 6, where each year is represented by different symbols. The scatterplots can be
349 divided into quadrants, the NE quadrant is Q1, the NW quadrant is Q2, the SW quadrant is Q3
350 and the SE quadrant is Q4. These quadrants are representative of certain meteorological dynamic
351 conditions. For instance, Q1 and Q3 are most likely associated with a well-mixed boundary layer
352 such that aerosols are well distributed throughout the atmospheric column, thus satellite and
353 ground-based measurements are in sync together. A vast majority of the data points lie within
354 Q3. Q3 contains points that have low AOD and good to moderate AQI. However, Q1 describes
355 data points with both high AOD and high PM_{2.5} measurements (i.e., orange and higher AQI).

356 The remaining two quadrants in most cases can distinguish between different sources of
357 air pollution. The points within Q2 have high AOD but low PM_{2.5} concentrations. This situation
358 could arise from long-range transport of aerosols into the area. The long-range transport of
359 aerosols generally occurs above the boundary layer. Subsequently, these aerosols do not
360 necessarily impact ground-based measurements (see discussion in previous section). However, it
361 is possible that those aerosols can become entrained within the boundary layer due to changing
362 dynamics and can impact ground-based measurements further downwind of the source. Finally,
363 Q4 has data points that coincide with high PM_{2.5} concentrations and relative low AOD. More
364 than likely, these points represent increasing PM_{2.5} concentrations of local source emissions. A

365 possible scenario where this could occur is a strong inversion. In late spring and summer in
366 Georgia strong inversions occur that trap all the local sources of pollution, e.g., cars and power
367 plants, close to the surface by hindering vertical mixing. Low-level aerosols are more difficult
368 for satellites to detect, and again this could lead to a satellite and ground-based measurement
369 mismatch.

370 We have discussed what factors could possibly influence the PM_{2.5}/AOD relationship; the
371 following analysis involves determining the robustness of the PM_{2.5}/AOD relationship through
372 correlations. For a majority of the stations, both Aqua and Terra are correlated with PM_{2.5}.
373 Correlation coefficients for Aqua vary between 0.37 – 0.76, and Terra has r-values of 0.25 – 0.68
374 (see Tables 4 and 5). MODIS Terra and Aqua produce correlations that are similar to each other.
375 In Tables 4 and 5, the correlation coefficient (r), the slope, y-intercept, and the number of
376 observations are summarized. In 2007, MODIS Terra and Aqua have the highest correlations
377 across all of the stations. The higher means of Terra AOD do not result in better agreement with
378 PM_{2.5}, except in 2007 where Terra has higher r-values than Aqua. Terra also produces more
379 variability in the correlation coefficients across the stations in comparison to Aqua. The
380 seasonality of AOD and PM_{2.5} is reflected in the values as well. Spring produces higher
381 correlations than summer. The results presented here are somewhat different than the results
382 from Gupta and Christopher¹¹. In their study, they presented correlations between estimated
383 PM_{2.5} from both a two-variable model and multivariate model. Our correlations and slopes show
384 more variance than their reported values. Some of the difference could be due to the different
385 time periods under consideration.

386 To determine how robust the AOD is at characterizing PM_{2.5}, the AQI designations of
387 PM_{2.5} concentrations are used to categorize the AOD. For instance, all AOD data points that
388 correspond to PM_{2.5} concentrations between 0 – 15.4 µgm⁻³ are considered to be good/green
389 AOD. This classification methodology is used for all six categories of AQI. This categorized
390 AOD is then used to determine a threshold that can probabilistically separate days of air quality
391 exceedances from days without exceedances.

392 Figures 7 and 8 show AQI classified Aqua/Terra MODIS AOD for 2004 – 2008. The top
393 figure is for Terra and the bottom is for Aqua. For Figure 7 the upper panels are green AOD and
394 the bottom panels are yellow AOD. The panels on the left are frequency histograms and on the
395 right are cumulative histograms of AOD. In Figure 7, green and yellow AOD have similar

396 frequency and cumulative distributions. The cumulative distributions for both satellites are
397 interpreted as 80% of Code Green AOD are below 0.35, and 80% of Code Yellow AOD are
398 below 0.65. In Figure 8 the upper panel is Code Orange AOD and if present the bottom panel is
399 Code Red AOD. Code Orange and Red AOD have different distributions. It is not surprising that
400 red AOD is skewed toward higher AOD. The closely related relationship between AOD and
401 $PM_{2.5}$ suggests that high AOD will occur in cases of high $PM_{2.5}$. Code Orange AOD is associated
402 with AOD of 0.75 for Aqua and 0.65 for Terra. The lack of Code Red AOD makes determination
403 of thresholds difficult.

404 The broad thresholds (80%) discussed above yielded overestimation in the orange and red
405 categories. To more accurately match the $PM_{2.5}$ -derived AQI we used different thresholds from
406 each satellite. For this we calculated AOD thresholds for Gwinnett for all years. The yearly
407 threshold levels, e.g., 80%, 90%, and 95% were averaged to create AQI categorized AOD
408 thresholds specifically tuned for Gwinnett. Figure 9 shows our AOD-derived AQI and $PM_{2.5}$ -
409 derived AOD at Gwinnett. Specifically for Terra we used the 80% threshold for green AQI and
410 95% for yellow and orange AQI. The exact cut-offs for Terra AOD are: green is below 0.26,
411 yellow is 0.26 – 0.72, orange 0.72 – 1.0, and red is everything greater than 1. For Aqua we used
412 the 80% threshold for green AQI and 90% for yellow and orange AQI. While AOD cut-offs for
413 Aqua are slightly different than for Terra. Aqua AOD thresholds are: green is below 0.28, yellow
414 is 0.28 – 0.69, orange is 0.69 – 1.15, and red is everything over 1.15.

415 While we only show pie charts based upon the new AQI designations, there are small
416 differences between them and pie charts produced with AOD-derived AQI using old
417 designations. The differences occur mostly within the yellow and orange AQI categories.
418 Though these figures are not an exact match for the $PM_{2.5}$ -based AQI, they provide information
419 at an easily understandable and relatable manner. Additionally, the best guesses used in
420 determining quadrants agree well with the probabilistic measures of AOD given by this type of
421 analysis. Having probabilistic means to describe the incidence of AOD over metro Atlanta
422 allows for this threshold approach to be extrapolated for use in areas without $PM_{2.5}$ monitors.
423 AQI categorized AOD has great applicability to rural areas in Georgia and the other rural areas
424 across the country, because this approach is not bound strictly by achieving high correlations
425 between $PM_{2.5}$ and AOD.

426 CONCLUSIONS

427 Utilization of remotely sensed data allows for a broader perspective view of air quality.
428 Local air quality is affected by a number of factors including regional emissions, temperature,
429 atmospheric dynamics, and traffic patterns. Satellite data also allows for viewing features that
430 could impact air quality in the near future. This research presented a multi-year analysis of spring
431 and summer data from 2004- 2008 in metropolitan Atlanta. Our research focused upon the
432 synergy between ground-based measurements of $PM_{2.5}$ and NASA satellite observations in the
433 terms of Aerosol Optical Depth (AOD) from MODIS and the Aerosol Index (AI) from OMI.
434 MODIS AOD (τ) is a derived measurement from both MODIS instruments onboard the Terra
435 and Aqua satellites. OMI onboard Aura is an instrument that measures the absorbing aerosols in
436 the UV-spectrum. Our research goals were to understand the variability within the $PM_{2.5}$ and
437 AOD data records, assess the strength of the $PM_{2.5}$ /AOD relationship, and probabilistically
438 determine AOD thresholds that relate directly to AQI categories.

439 Results for the $PM_{2.5}$ analysis show that $PM_{2.5}$ differences are likely due to station
440 location, with the highest averages of $PM_{2.5}$ occurring at an urban site and the lowest averages
441 occurring at a rural site. The spring months show less variability than summer months in the
442 $PM_{2.5}$ record. MODIS AOD has captured the same yearly behavior shown in $PM_{2.5}$, yet on a
443 seasonal basis the summertime has AOD values double that of the spring. Remotely sensed data,
444 such as MODIS AOD, are a valuable tool for use in air quality applications. Our results suggest
445 that SOA formation in the region could have an impact on local $PM_{2.5}$ concentrations. Satellite
446 data are uniquely able to provide information about SOA levels on an almost daily basis. This
447 information could aid air quality forecasters by allowing them to fine tune their models to more
448 accurately describe conditions in the U.S. Southeast. OMI AI does not have a discernable
449 seasonal component. Background levels of AI for the metro area are around 0.3. Eighty percent
450 of AI is below 0.5, therefore, AI values significantly higher than this could be indicative of long-
451 range aerosol transport into the area. The results of linear regressions between $PM_{2.5}$ and AOD
452 are r-values above 0.5 for a majority of sites. Interestingly, Terra produced higher correlation
453 coefficients than Aqua in 2007, while in other years the satellites have similar r-values. We
454 propose using statistical analysis of AOD data to relate AOD directly to AQI via probabilistic
455 measures based upon past AOD values for a specific area. The research also determined that
456 80% of Code Green days occur with AOD of 0.35 or less, and 80% of Code Yellow days occur

457 with AOD of 0.65. These probabilistic AOD cutoffs can be used to quickly access the AQI
458 classifications without the dependence upon ground-based measurements. There is some
459 agreement between PM_{2.5} based AQI and satellite based AQI. Further work will need to be done
460 to better tune the methodology for orange and red AQI.

461 Future plans are to continue this type of analysis using the data from the Multi-angle
462 Imaging SpectroRadiometer (MISR) instrument onboard Terra. A portion of that research would
463 be a comparison between MODIS and MISR in the U.S. southeast. Additional analysis would be
464 done to apply the proposed probabilistic approach with MISR data. Also, the methodology for
465 using AOD thresholds to understand general tendencies about AQI can be tuned to specific
466 states, regions, and areas with few PM_{2.5} measurements. The data from these satellites also
467 provide an important means for determination and understanding of "normal" conditions, which
468 can allow air quality policy makers to make better use of satellite data for possible application to
469 the U.S. EPA's Clean Air Interstate Rule as well as the exception events rule for NAAQS
470 designations.

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476

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567 **TABLES**

568

AQI Category	Color	Index Values	PM _{2.5} 24-hour (µg/m ³)	
			Current	Proposed
Good	Green	0 - 50	0.0 - 15.4	No change
Moderate	Yellow	51 - 100	15.5 - 40.4	15.5 - 35.4
Unhealthy for Sensitive Groups	Orange	101 - 150	40.5 - 65.4	35.5 - 55.4
Unhealthy	Red	151 - 200	65.5 - 150.4	55.5 - 150.4
Very Unhealthy	Purple	201 - 300	150.5 - 250.4	No change
Hazardous	Maroon	301 - 400	250.5 - 350.4	No change
		401 - 500 (this level used for emergency episode planning only.)	350.5 - 500	No change

569 **Table 1.** AQI designations. Source: U.S. EPA

570

Location	2004		2005		2006		2007		2008	
	Terra	Aqua								
Con. Ave.	-	-	18.61	18.87	23.63	21.25	23.42	21.31	20.68	17.89
Gwinnett	16.69	14.12	17.72	15.63	19.94	17.02	21.64	17.22	15.90	13.70
McDonough	17.26	14.74	18.41	16.59	21.13	17.32	21.54	16.63	17.29	13.51
Newnan	16.63	14.14	18.05	16.14	19.94	16.10	22.55	17.01	17.13	14.29
S. Dekalb	17.24	14.33	18.54	15.50	19.20	16.96	23.04	21.42	18.22	15.42
Walton	-	-	16.80	15.23	18.81	16.48	19.70	15.79	15.84	13.17
Yorkville	14.86	14.64	16.30	16.24	18.60	16.87	19.45	19.33	14.30	13.58

571 **Table 2.** Means of PM_{2.5} concentrations for each station. Bold numbers are significantly different from each other for $\alpha = 0.05$.

572

Year	Season	r		#	
		Terra	Aqua	Terra	Aqua
2005	Spring	-0.13	-0.05	57	53
	Summer	0.06	0.23	46	48
2006	Spring	-0.12	-0.09	65	64
	Summer	0.30	0.42	66	67
2007	Spring	0.03	-0.13	65	69
	Summer	0.08	0.10	58	61
2008	Spring	-0.35	-0.31	60	62
	Summer	0.18	0.15	60	59

573 **Table 3.** Correlation coefficient and number of observations for OMI AI vs. MODIS AOD

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Location	Year	2004		2005		2006		2007		2008	
	Season	Spring	Summer								
Confederate Ave.	Slope	-	-	0.03	0.01	0.01	0.01	0.02	0.02	0.00	0.01
	Y-intercept	-	-	-0.24	0.30	-0.05	0.14	-0.12	-0.03	0.11	0.11
	r	-	-	0.87	0.22	0.62	0.37	0.81	0.62	0.15	0.44
	#	-	-	6	35	59	66	57	53	54	61
Gwinnett	Slope	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.02	0.01	0.01
	Y-intercept	-0.05	0.13	-0.02	0.23	0.00	0.11	-0.01	0.08	0.10	0.16
	r	0.68	0.51	0.66	0.50	0.62	0.44	0.76	0.67	0.29	0.41
	#	53	48	46	38	67	53	61	53	54	63
McDonough	Slope	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.01
	Y-intercept	-0.03	0.09	0.04	0.25	0.02	0.18	-0.05	0.03	0.09	0.17
	r	0.54	0.64	0.51	0.38	0.53	0.40	0.70	0.67	0.25	0.34
	#	54	44	56	39	57	70	59	59	51	61
Newnan	Slope	0.01	0.01	0.01	0.00	0.01	0.01	0.02	0.02	0.00	0.01
	Y-intercept	0.00	0.16	0.02	0.28	-0.03	0.21	-0.05	0.09	0.11	0.08
	r	0.44	0.46	0.57	0.30	0.73	0.37	0.78	0.61	0.16	0.56
	#	55	32	40	35	57	63	57	57	49	62
S. Dekalb	Slope	0.01	0.01	0.01	0.00	0.01	0.01	0.02	0.02	0.01	0.01
	Y-intercept	-0.02	0.14	0.06	0.33	-0.01	0.15	-0.04	-0.03	0.10	0.19
	r	0.54	0.49	0.56	0.22	0.59	0.40	0.78	0.69	0.19	0.33
	#	54	44	56	35	55	63	59	55	54	66
Walton	Slope	-	-	0.01	0.00	0.01	0.02	0.02	0.02	0.01	0.01
	Y-intercept	-	-	-0.03	0.28	0.03	0.06	-0.03	0.05	0.05	0.19
	r	-	-	0.65	0.28	0.51	0.51	0.76	0.68	0.35	0.23
	#	-	-	32	36	55	64	53	56	49	59
Yorkville	Slope	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.02	0.01	0.01
	Y-intercept	-0.02	0.08	-0.04	0.24	-0.06	0.08	-0.05	0.00	0.03	0.11
	r	0.45	0.60	0.74	0.38	0.62	0.51	0.74	0.76	0.50	0.51
	#	55	42	47	40	57	60	55	57	50	57

Table 4. Slope, Y-intercept, correlation coefficient, and number of observations of seasonal PM_{2.5,24} vs. MODIS Terra AOD. Dash denotes missing data. Bold numbers are significant at $\alpha = 0.05$.

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578

Location	Year	2004		2005		2006		2007		2008	
		Spring	Summer								
Confederate Ave.	Slope	-	-	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01
	Y-intercept	-	-	0.10	0.29	-0.09	0.11	0.03	0.02	-0.09	0.07
	r	-	-	0.18	0.37	0.70	0.41	0.54	0.51	0.54	0.51
	#	-	-	6	42	57	59	45	47	49	58
Gwinnett	Slope	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.01
	Y-intercept	0.00	0.19	0.10	0.21	-0.04	0.11	0.10	0.10	0.02	0.14
	r	0.51	0.40	0.39	0.49	0.70	0.46	0.56	0.59	0.46	0.46
	#	60	54	47	44	60	50	51	50	48	67
McDonough	Slope	0.02	0.01	0.01	0.01	0.02	0.01	0.02	0.02	0.01	0.01
	Y-intercept	-0.07	0.12	0.08	0.29	-0.02	0.14	-0.01	0.07	-0.02	0.07
	r	0.56	0.54	0.47	0.38	0.67	0.46	0.62	0.65	0.58	0.53
	#	58	46	49	43	54	58	43	55	52	61
Newnan	Slope	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.02	0.01	0.01
	Y-intercept	-0.01	0.23	0.12	0.21	-0.05	0.17	-0.02	0.09	0.05	0.15
	r	0.40	0.43	0.26	0.56	0.70	0.45	0.71	0.61	0.37	0.50
	#	56	38	39	44	57	56	42	52	49	58
S.Dekalb	Slope	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.01	0.01
	Y-intercept	0.02	0.13	0.10	0.30	-0.07	0.09	0.05	0.01	0.02	0.06
	r	0.41	0.52	0.42	0.42	0.76	0.54	0.53	0.63	0.40	0.56
	#	60	48	51	42	54	55	46	53	52	61
Walton	Slope	-	-	0.01	0.01	0.02	0.02	0.01	0.02	0.01	0.01
	Y-intercept	-	-	0.14	0.23	-0.04	0.06	0.07	0.08	0.02	0.04
	r	-	-	0.23	0.41	0.61	0.51	0.50	0.63	0.42	0.51
	#	-	-	36	39	52	61	44	50	45	57
Yorkville	Slope	0.02	0.02	0.01	0.01	0.02	0.02	0.01	0.02	0.02	0.01
	Y-intercept	-0.01	0.06	0.04	0.20	-0.02	0.06	0.08	0.05	-0.04	0.15
	r	0.41	0.59	0.51	0.56	0.59	0.57	0.49	0.72	0.59	0.47
	#	52	44	44	42	58	53	49	55	50	61

579 **Table 5.** Slope, Y-intercept, correlation coefficient, and number of observations of seasonal PM_{2.5,24} vs. MODIS Aqua AOD.
 580 Dash denotes missing data. Bold numbers are significant at $\alpha = 0.05$.

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LIST OF FIGURES

Figure 1. Bar plots of yearly averaged $PM_{2.5}$ at Gwinnett (a) and Newnan (b). Green dashed line represents $PM_{2.5,T}$ five-year average, and blue dashed line represents $PM_{2.5,A}$ five-year average. Bar plots of seasonally averaged $PM_{2.5}$ at Gwinnett (c) and Newnan (d).

Figure 2. Scatterplots of $PM_{2.5,T}$ vs. $PM_{2.5,A}$. Red line represents 1:1 correspondence.

Figure 3. Bar plots of yearly averaged MODIS AOD at Gwinnett (a) and Newnan (b). Green dashed line represents MODIS Terra five-year average, and blue dashed line represents MODIS Aqua five-year average. Bar plots of seasonally averaged MODIS AOD at Gwinnett (c) and Newnan (d).

Figure 4. Scatterplots of OMI AI vs. MODIS Terra/Aqua AOD. Red line represents 1:1 correspondence. Rectangular boxes are discussed in text.

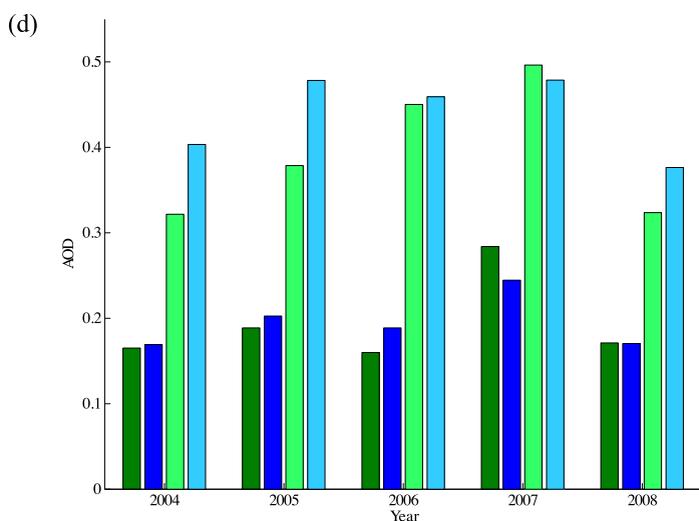
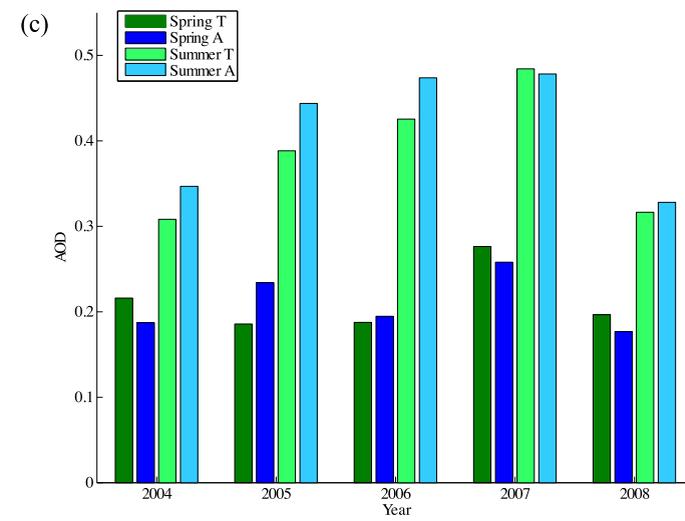
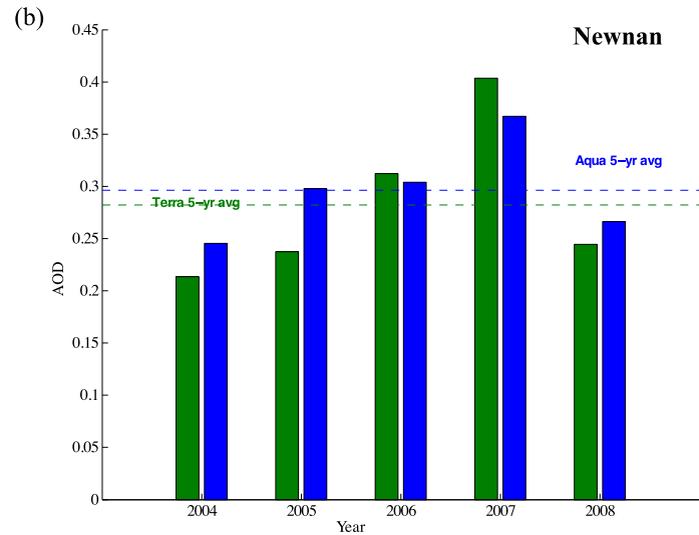
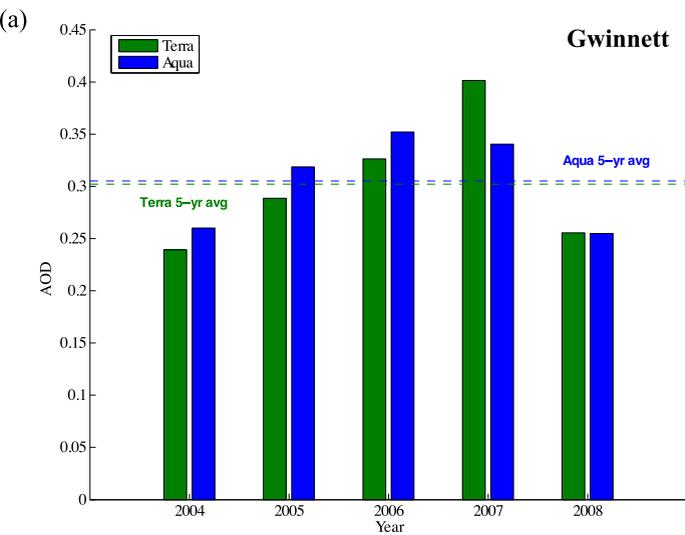
Figure 5. Scatterplots of MODIS Aqua AOD vs. MODIS Terra AOD. Red line represents 1:1 correspondence.

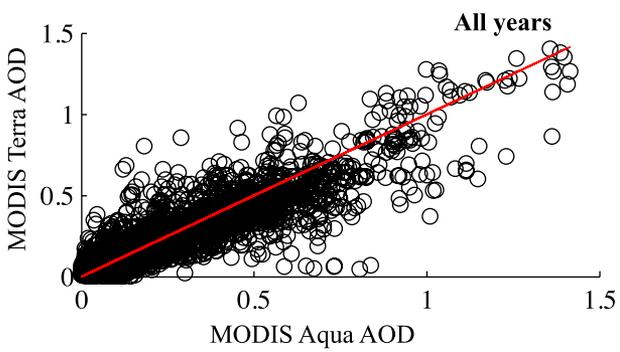
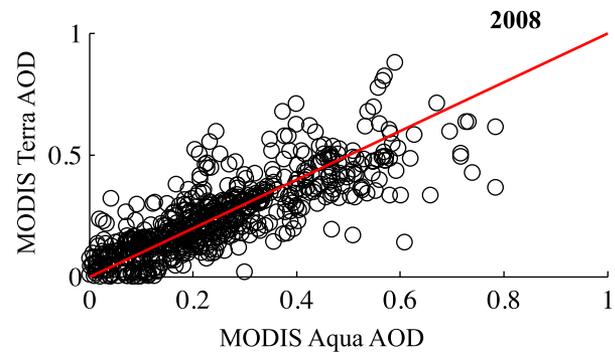
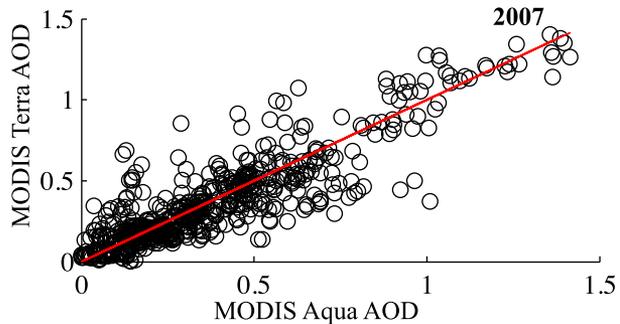
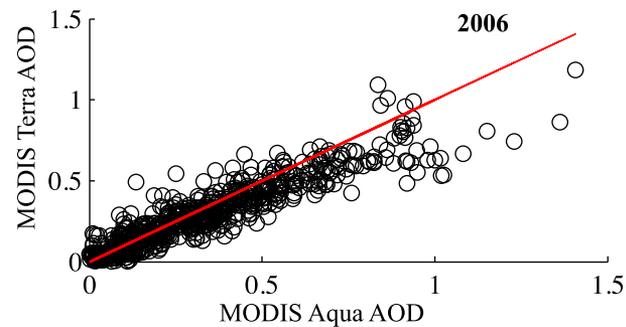
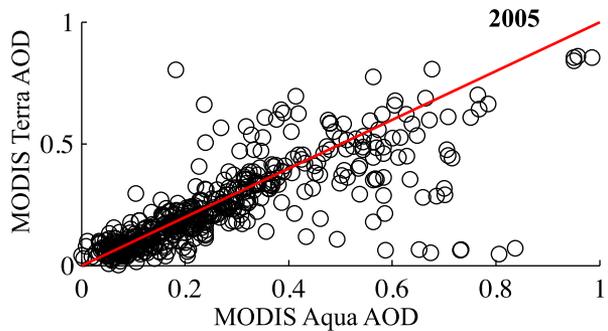
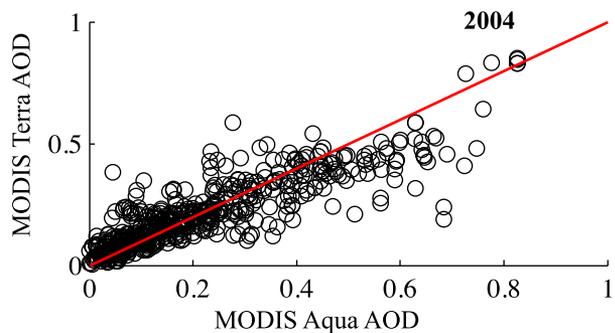
Figure 6. Scatterplot of $PM_{2.5,24}$ vs. MODIS Aqua AOD.

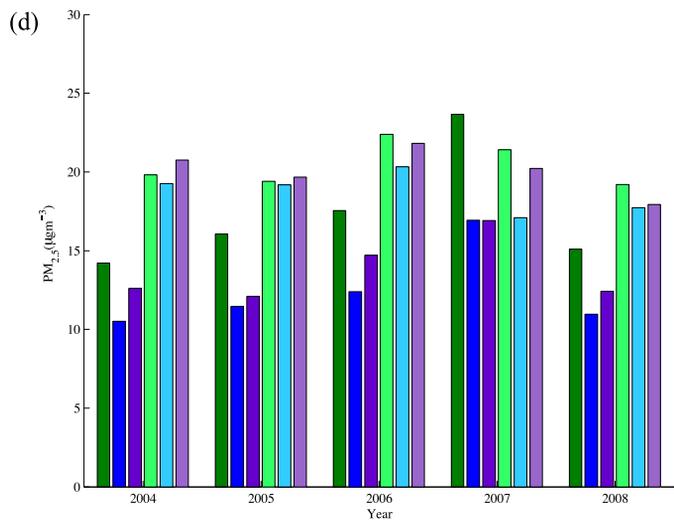
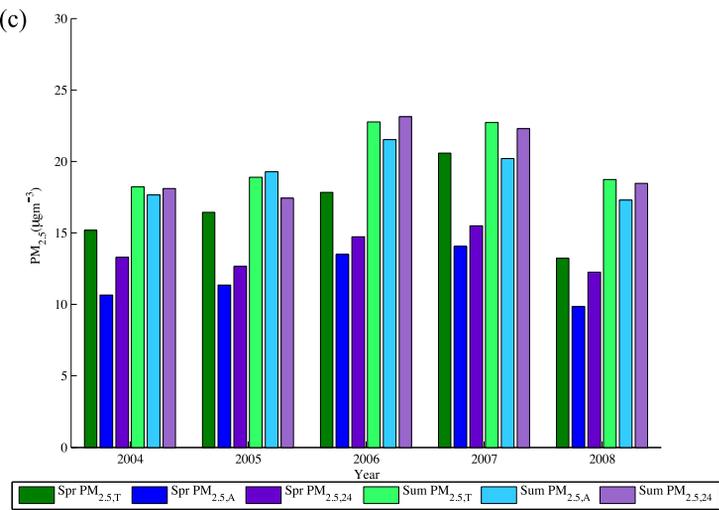
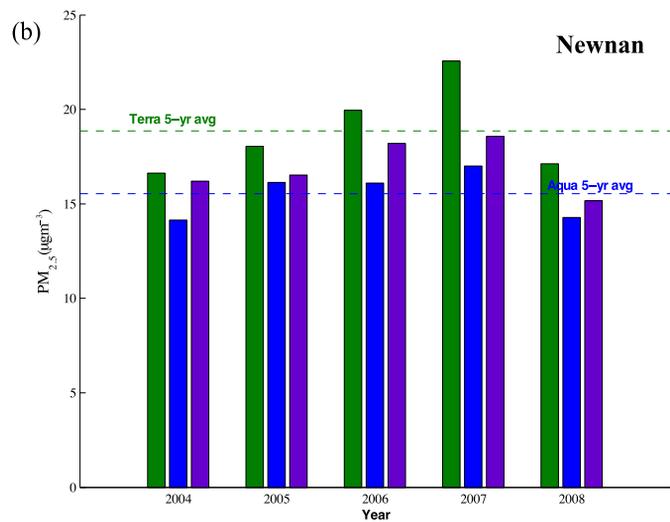
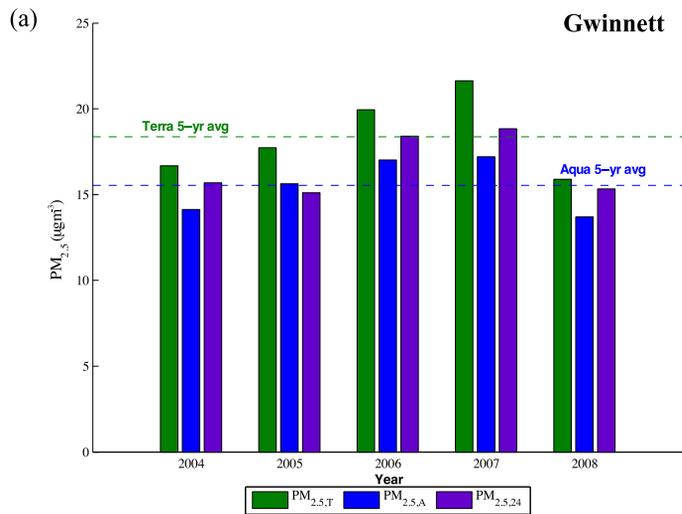
Figure 7. (a) Relative frequency histograms and cumulative sum histograms of Code Green and Code Yellow Terra AOD for 2006. (b) Relative frequency histograms and cumulative sum histograms of Code Green and Code Yellow Aqua AOD for 2006.

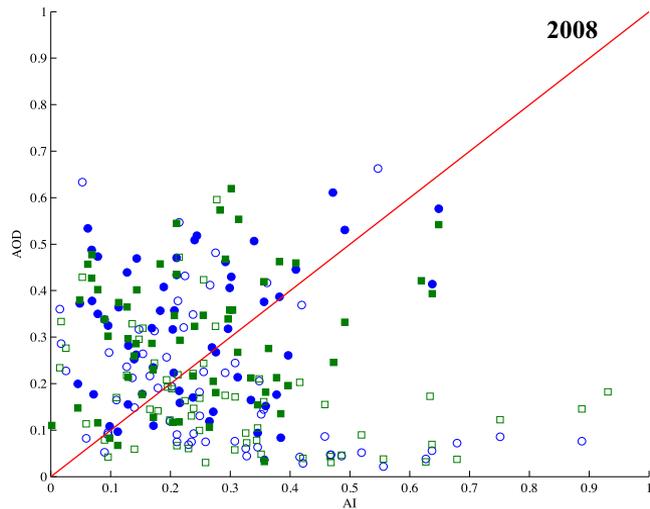
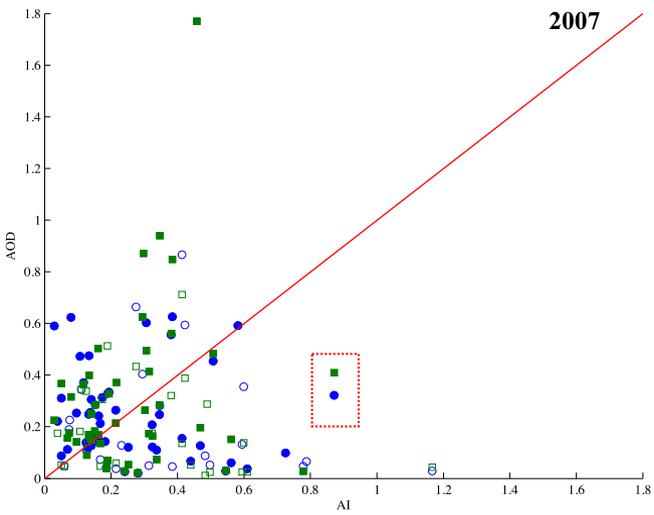
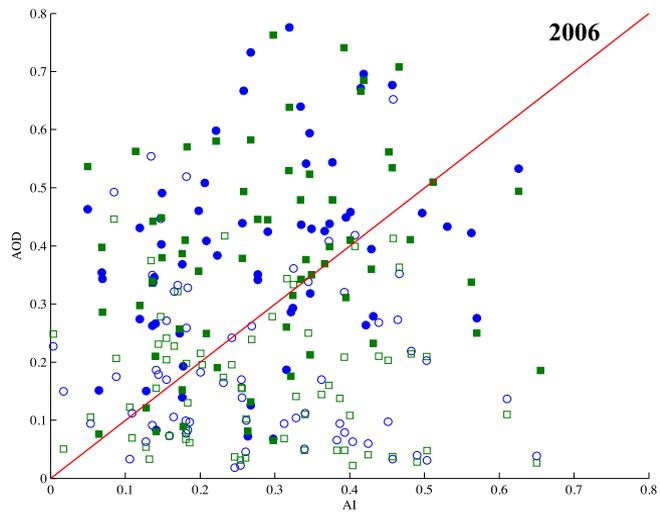
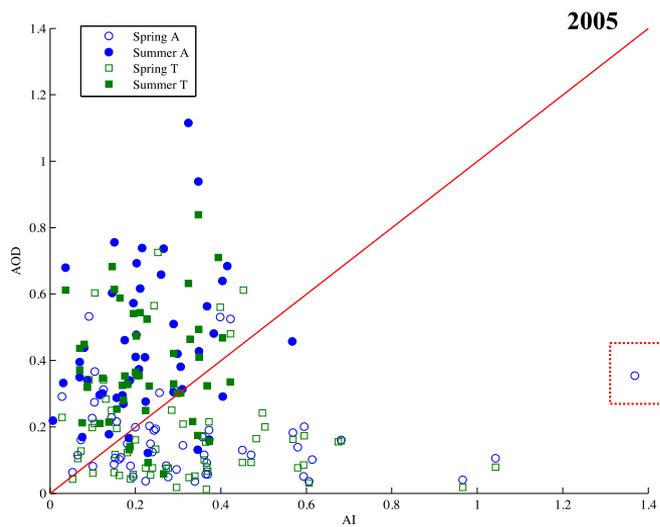
Figure 8. (a) Relative frequency histograms and cumulative sum histograms of Code Orange and Code Red Terra AOD for 2006. (b) Relative frequency histograms and cumulative sum histograms of Code Orange Aqua AOD for 2006.

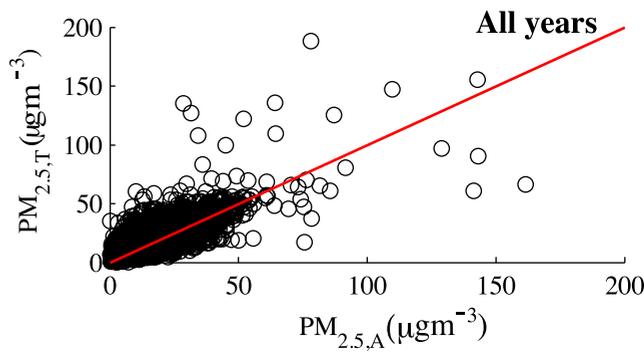
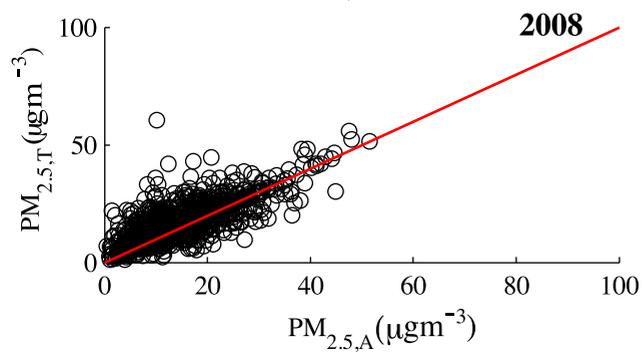
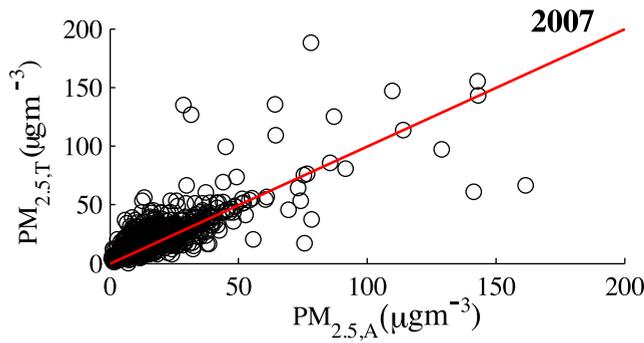
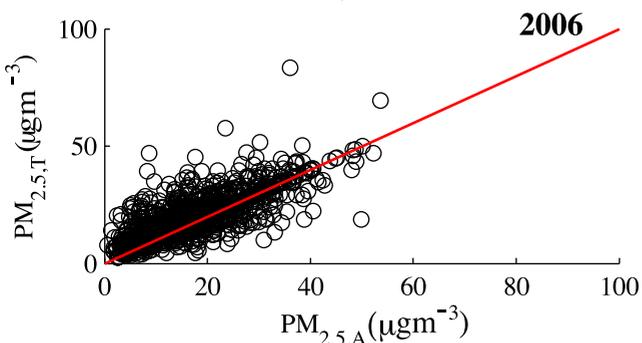
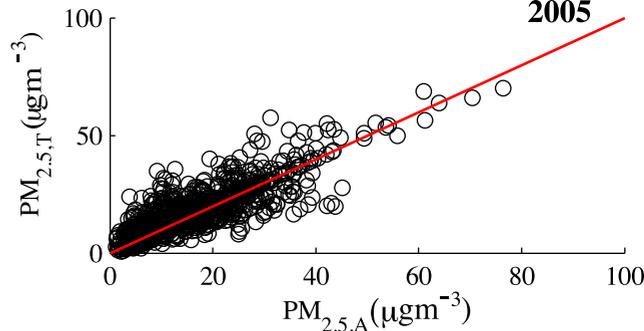
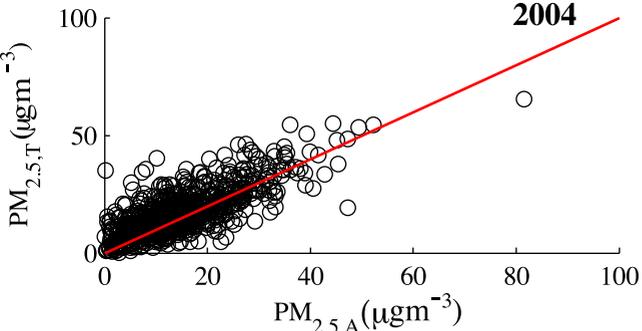
Figure 9. Piecharts of $PM_{2.5}$ -derived AQI, MODIS Terra-derived AQI, and MODIS Aqua-derived AQI at Gwinnett in 2006.

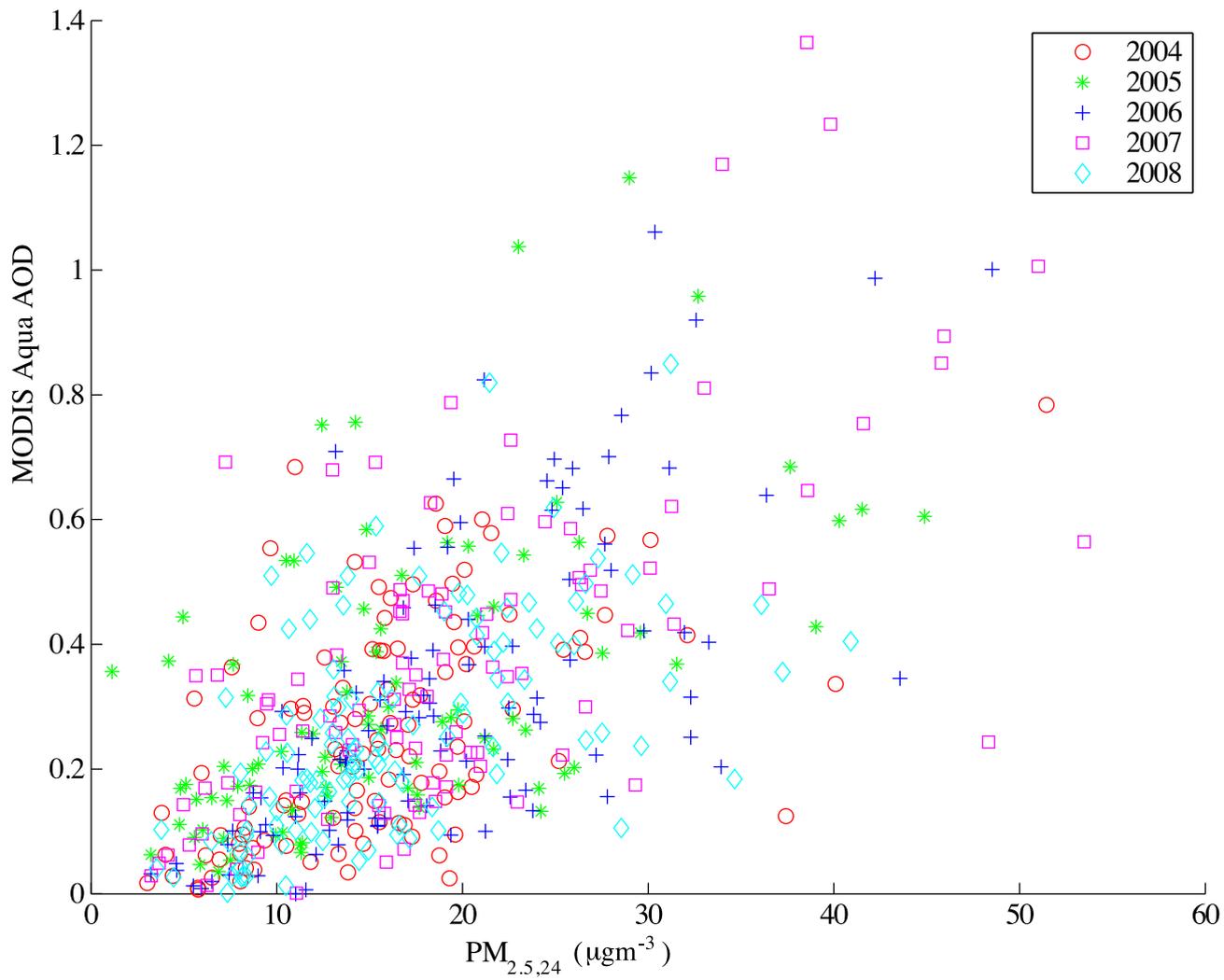




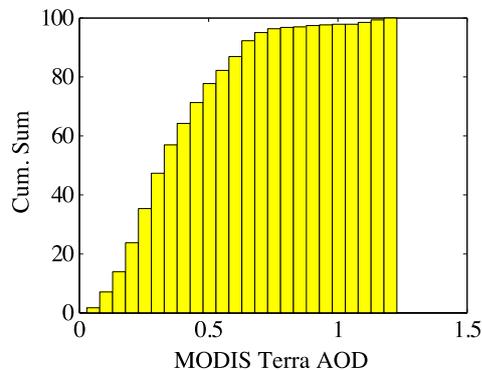
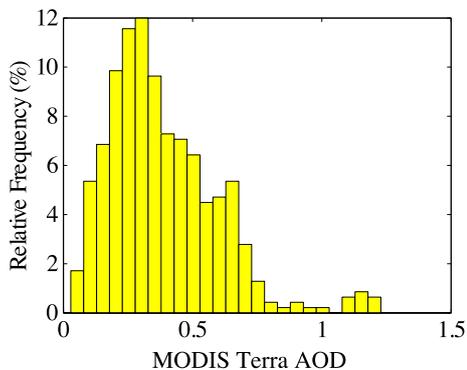
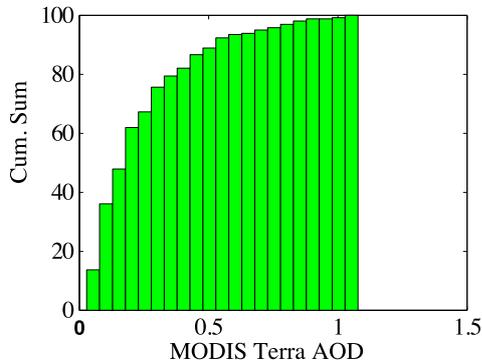
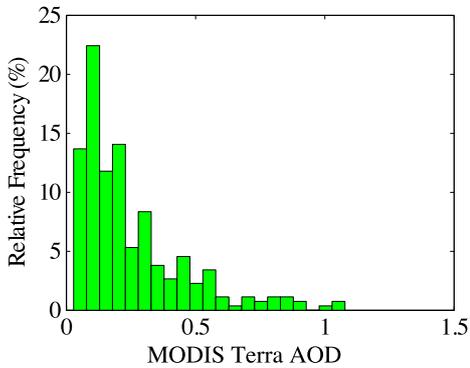




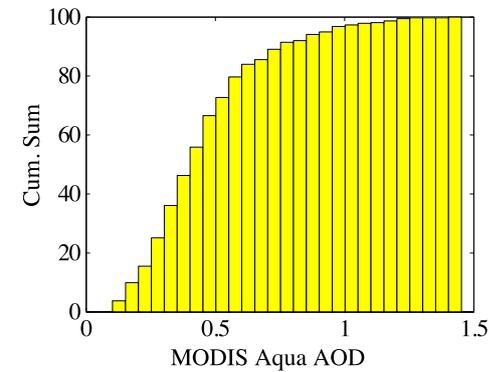
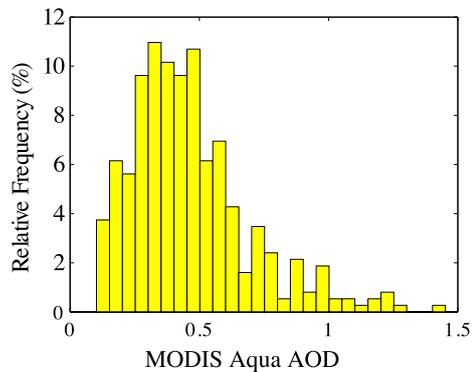
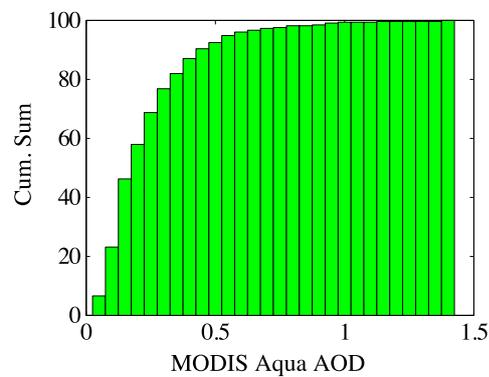
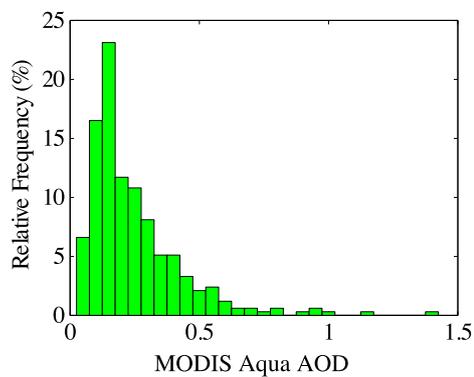




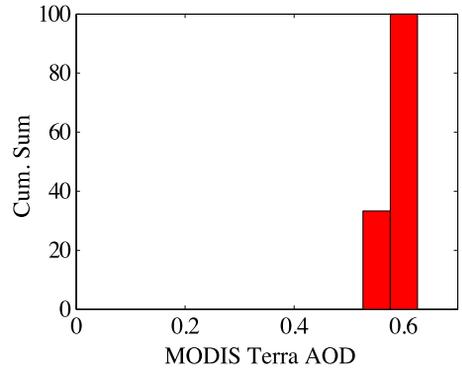
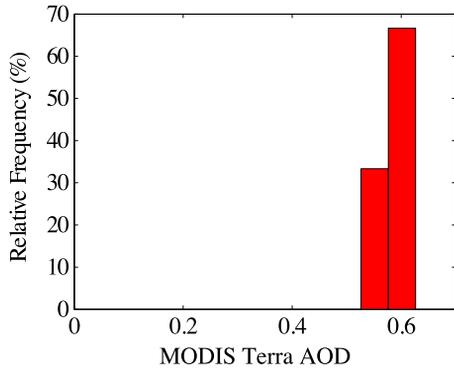
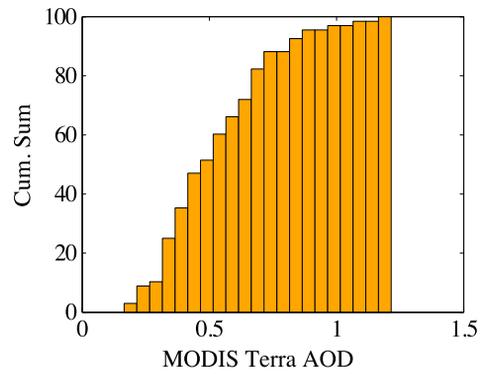
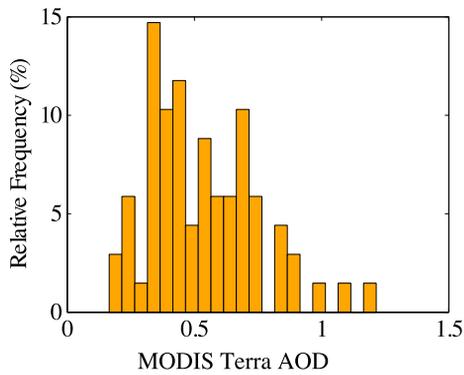
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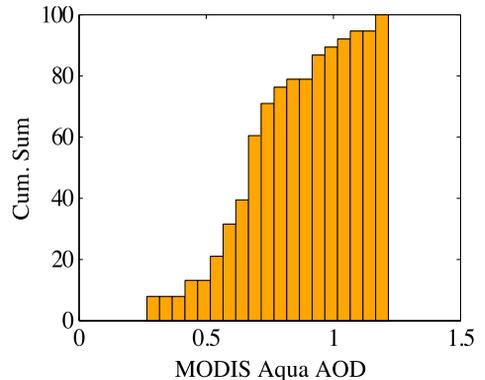
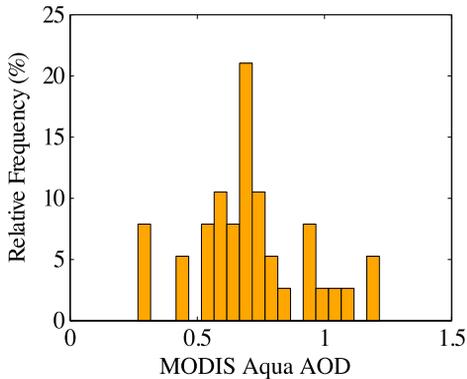
(b)



(a)



(b)



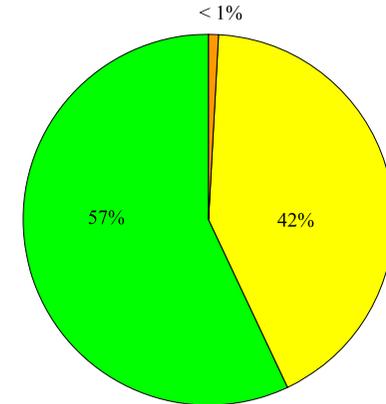
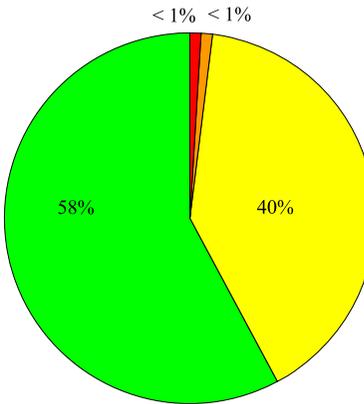
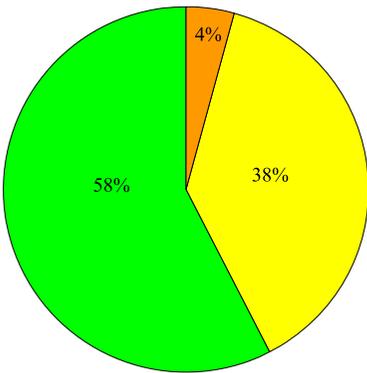


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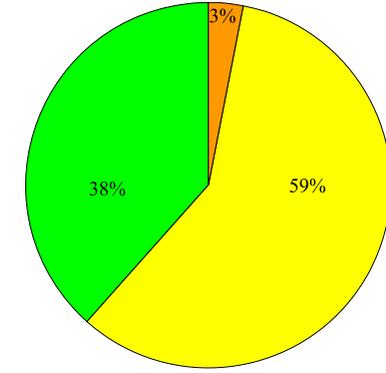
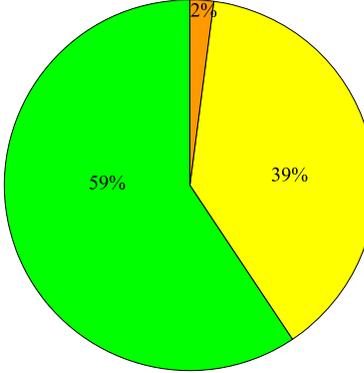
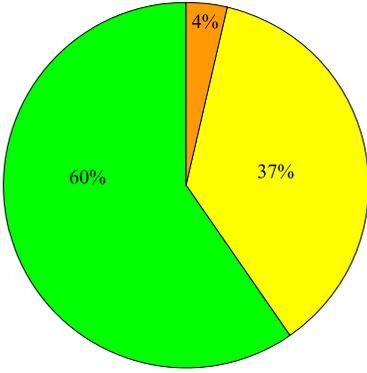
AQI from Terra AOD

AQI from Aqua AOD

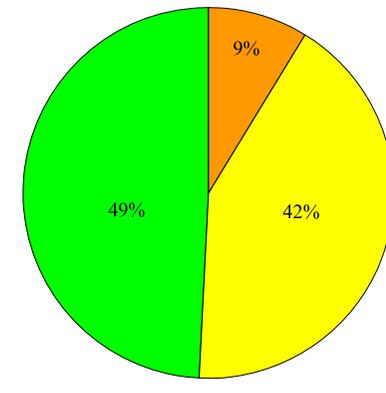
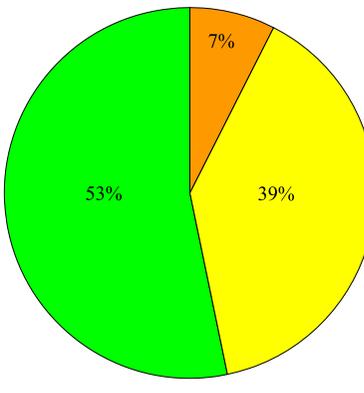
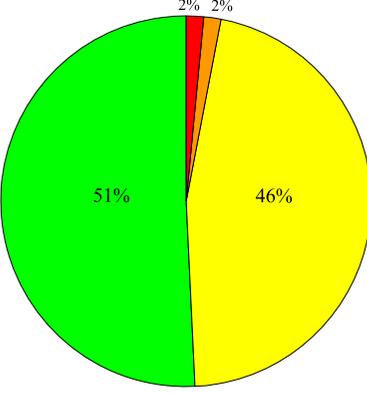
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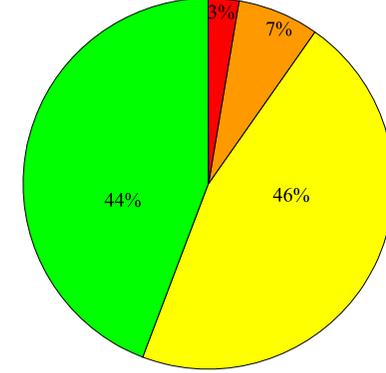
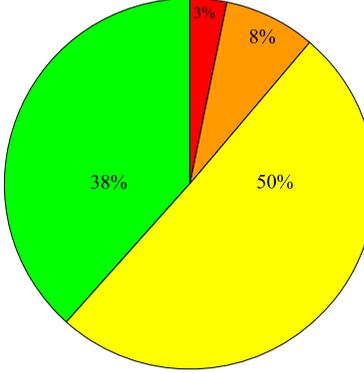
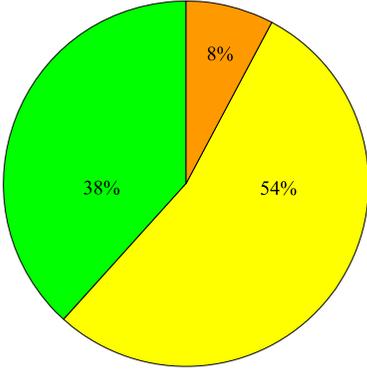
2005



2006



2007



2008

